Well-being across America: Evidence from a Random Sample of One Million U.S. Citizens

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Abstract

This paper uses new Behavioral Risk Factor Surveillance System data to provide the first estimates of well-being across the states of America. From this sample of 1.3 million US citizens, we analyze measures of life satisfaction and mental health. Controlling for people's characteristics, Louisiana and DC have high psychological well-being levels while California and West Virginia have low well-being. There is no correlation between states' well-being and their GDP per capita. Correcting for people's incomes, satisfaction with life is lowest in the rich states. We discuss implications for the arbitrage theory that regions provide equal utility and compensating differentials.

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"By the mid-twentieth century … people as a whole were not disease-ridden, and ideas of so-called positive health emerged. This emboldened the WHO to define health in a new way as 'physical, mental and social well-being, not merely the absence of disease or infirmity'…Medicine would then focus on improving health in the sense of (i) moving people toward the favorable end of the health spectrum, as determined subjectively by responses to questions, and (ii) enhancing the bodily reserves, as determined by screening tests".

Lester Breslow (1972): Dean, School of Public Health, UCLA.

1. Introduction

The topic of human well-being is important and one of cross-disciplinary interest. Recent research -- across a variety of literatures within the social and medical sciences -- has attempted to gauge the satisfaction and happiness of a society by drawing upon data both on citizens' subjective well-being and on measurements of variables such as real income. This work may have significant policy applications[1]. At the time of writing, for example, the Stiglitz Commission set up by Nicholas Sarkozy of France is about to complete a report on the issue of how in the future some mixture of economic prosperity and psychological health might be measured.

This paper is an empirical study of well-being in the United States. Its contribution is to examine mental health and life satisfaction among a recent random sample of 1.3 million US inhabitants. The size of the data set, gathered between 2005 and 2008, provides advantages denied to previous investigators. (The often-used General Social Survey, for example, samples only approximately 3,000 Americans bi-annually). We are able to establish some of the first evidence that the states of California, Kentucky, Michigan, Ohio, West Virginia and Missouri have relatively low levels of psychological well-being. These six states come within the lowest

[1] See the arguments in Argyle (2001), Dolan and Peasgood (2008), Gilbert (2006), Layard (2005), and Oswald (1997).

quartile of (regression-corrected) well-being on two separate measures. Using the same criteria, we show that Louisiana, D.C., Colorado, Alaska and Tennessee have relatively high well-being. The paper discusses the implications of these state-by-state patterns and demonstrates that there is no correlation between states' (regression-adjusted) levels of life satisfaction and their levels of GDP per capita. It also checks, and occasionally goes on to disagree with, some of the famous micro findings in the earlier US well-being literature. Following Easterlin (1974, 2003), and an emerging literature that includes Clark (2003), Di Tella et. al. (2001, 2003), Blanchflower and Oswald (2004), Kahneman et. al. (2004), Layard (2005), Deaton (2008), Levinson (2009), Daly and Wilson (2009), Stevenson and Wolfers (2009) and Luechinger (2009), we consider survey well-being data as proxy utility measures.

The paper focuses on five questions.

(i) Do some parts of the USA offer higher utility than others? We tackle this by combining information on people's reported levels of life-satisfaction and mental ill-health. Our conclusion is, broadly, yes.

(ii) Are the richer states also the happier states? We do not find evidence of this. In one circumstance, where individuals' own income is held constant, high GDP states are discernibly less happy. This is what compensating-differentials theory would predict.

(iii) Do life-satisfaction regression equations have the same econometric structure as mental-health equations? The approximate answer is that they do. Nevertheless, some exceptions emerge.

(iv) Economists would predict that well-being should be the same everywhere (because individuals can be expected to keep moving into attractive places until those are too congested and expensive to be desirable). This is a form of arbitrage argument and has a long intellectual pedigree going back to Adam Smith. How well does it hold empirically? Our evidence suggests not fully.

(v) How large are the estimated effects on individuals of personal variables such as income, race, and age? There is, in the literature, continuing debate about these variables' roles.

A question of longstanding interest to economists is about the links between income and well-being. The neoclassical textbook apparatus would suggest a strong connection: greater income allows the individuals access to greater resources and hence to higher utility. By contrast, the standard view in the psychology literature, well expressed by the review article of Diener and Biswas-Diener (2002), is that empirically there is only a slight correlation. In the studies those authors describe, the highest correlation that any American research has found is a Pearson's correlation coefficient of r = 0.18.

Another area of recent debate centers on the connections between aging and well-being. Traditional psychology, represented by sources such as Diener et. al.. (1999) and Argyle (2001), argues that happiness is either flat or slightly increasing in age. Some work by economists and others, however, has demonstrated signs of a U-shape through the life cycle. This result appears in Theodossiou (1998), Winkelmann and Winkelmann (1998), Frey and Stutzer (2002), Clark (2003), Blanchflower and Oswald (2004), Graham (2005), Oswald (1997), Sacker and Wiggins (2002), Van Praag and Ferrer-i-Carbonell (2004), Shields and Wheatley Price (2005), Oswald and Powdthavee (2007), and Propper et. al. (2005).

Use of American data on this issue has not been common. But one approach is that of researchers such as Mroczek and Kolanz (1998) and Easterlin (2006), who hold constant few or no other influences upon well-being, and instead look at the uncorrected relationship between happiness and age. In a sense, these authors focus on a reduced-form issue. That issue is a descriptive question: how does observed happiness vary over the life cycle? Further analysis includes that of Mroczek and Spiro (2005). The authors conclude in a data set on American veterans that happiness rises into the person's approximately early 60s, and then tends to fall away. As the youngest person in their data set is 40 years old, it is not easy to compare the result with that from a full random sample. New work by Glenn (2009) also argues, in his criticism of the multi-country study by Blanchflower and Oswald (2008), that there is no U shape in American data.

Our paper is in a broad intellectual tradition that includes Schkade and Kahneman (1998), Plaut et. al. (2002), Gabriel et. al. (2003), Propper (2005), Weich et. al. (2005), Powdthavee (2006), Moro et. al. (2008), and Luechinger (2009)[2]. Our results are compatible with new European analysis, done independently and with a slightly different statistical method, by Pittau et. al. (2009). Finally, Moriarty et. al. (2009) also recently draw on several waves of the BRFSS data used in this paper to look at geographical patterns in serious mental illness across U.S. states.

2. Theoretical issues

An old idea in the economics literature is that different regions within a country can be expected to provide the same level of utility to their inhabitants.[3] If Vermont, for example, offers a more attractive level of well-being to representative Individual A than does Ohio, then we would expect to see Ohio citizens like Individual A try to move into the Vermont area. That kind of migratory flow will

2 Propper et. al. (2005) and Weich et. al. (2005) find little geographical variation in mental health once they control for micro characteristics of people.

cease only when a receiving region has become less desirable as an area in which to live. The economic equilibrium ought to be one of strict equality of utility (Roback 1982, Hoehn et. al. 1987). This is a theoretical proposition. It rests on the assumptions of, first, sufficiently low mobility costs and, second, sufficiently accurate levels of information about what it would be like to live in another state.[4] It is also possible that the proposition holds only after a considerable adjustment period (Treyz et. al. 1993). If the economist's arbitrage theory across regions is correct, and well-being data are a useful proxy for utility, then its prediction should be detectable in an empirical test for state-by-state equality of well-being for a person of given characteristics. When might such a test ever be expected to fail? One such circumstance would be after a major change in events or the intrinsic attractiveness of individual states or regions.

3. Data

We explore these issues empirically. To do so, we draw upon data collected under the auspices of the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a state-based system of health surveys that collects information on health risk behaviors, preventive health practices, and health care access primarily related to chronic disease and injury. For many states, the BRFSS is the only available source of timely, accurate data on health-related behaviors. BRFSS was established in 1984 by the Centers for Disease Control and Prevention (CDC); currently data are collected

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[3] This point does not seem often to be made in the general social science literature on area effects (such as Plaut et. al. 2002 or Propper et. al. 2005).

[4] Technically, the standard arbitrage argument is that the marginal values of some variable X should be equated. Consider a much older world where people can live anywhere in the USA and wherever they go they can claim some land for free. Then early migrants into California claim the beach properties and therefore, even after some years, average happiness in California is higher than in, say, Idaho. In this case there can be a difference between the marginal and average citizen's utility because early movers have an advantage. But now assume that in the modern era everything is tradable. Hence even a new migrant to California who has sufficient resources can acquire a beach

monthly in all 50 states, the District of Columbia, Puerto Rico, the U.S. Virgin Islands, and Guam. The data are designed to "identify emerging health problems, establish and track health objectives, and develop and evaluate public health policies and programs." States also use BRFSS data to support health-related legislative efforts. More than 350,000 adults are interviewed each year, making the BRFSS the largest telephone health survey in the world. We limit our sample to respondents between the ages of 18 and 85 with non-missing information. The data set's annual samples provide statistically representative snapshots of the U.S. Information on individual life-satisfaction was collected in BRFSS for the first time in 2005. Hence there has been little published research on life-satisfaction using this data set.

In the remainder of the paper, we rely on two particular questions. One provides information about how people feel generally about the quality of their lives; the other gets more narrowly at their mental health. The exact wording of the BRFSS life-satisfaction question is: *"In general, how satisfied are you with your life?"* Here people are able to answer one of the following: Very Satisfied, Satisfied, Dissatisfied, or Very Dissatisfied [Questionnaire line code 206]. The wording of the mental health question [Questionnaire line code 76] that we use as a complementary source of well-being information is: "*Thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"* In this case, individuals report an integer between zero and 30.

Within the BRFSS questionnaire, individuals are asked quite early on about their days of poor mental health. Eight pages (of questions) later, they are asked

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property. Then, controlling for people's characteristics, the 'marginal' Californians are as happy as all other Californians.

about their household income. Twelve pages after the income question, they are asked about their feelings of satisfaction with their own life.

The paper's evidence is set out in four main tables. These give regression equation results in which the dependent variable is derived from the two kinds of survey answers. To give a feel for the raw patterns in the data, life satisfaction in the United States can be treated in a cardinal way by assigning 1 to 4 to the four answers, where 'very satisfied' is assigned a 4. The mean of life satisfaction in modern US data is then 3.4, with a standard deviation of 0.6. The median number of days of mental ill-health is zero, while the mean is 3.4 days in the last month, with a standard deviation of 7.7. Well-being answers are thus skewed, in both kinds of measures, towards the upper end of the possible well-being distribution. Appendix Table A1 describes the means in the data set.

4. Results

Life-satisfaction equations, in which the years 2005-2008 are pooled, are set out in Table 1. For simplicity and to maintain comparability with some of the early literature, we choose to use here an elementary linear OLS estimator in which the four possible values of the dependent variable are assigned the integers from a high of 4 down to a low of 1. The later substantive findings are not altered by switching to an ordered estimator. The simplicity of Table 1's method allows coefficient sizes to be read off directly as life-satisfaction points.

Column 1 of Table 1 reveals a monotonic relationship between household income and people's feelings of satisfaction with their lives. The omitted category is a household income under $10,000 per annum. Seven dummy variables are included, for income bands stretching up to "income greater than $75,000". It can be seen that, perhaps unsurprisingly given the sample size, the null of zero on these coefficients can be rejected at any conventional level (the implied t-statistic on the upper-income banded dummy, for example, exceeds 200).

The size of the income gradient in Table 1 is large. There are four ways to view this. First, if we compare Americans with the lowest levels of income to those with the highest levels, the difference in life-satisfaction in column 1 is approximately 0.6 points. To put this in context, only approximately 5% of the sample put themselves in the two lower satisfaction categories (dissatisfied with life; very dissatisfied with life), so a hypothetical change of 0.6 life satisfaction points is to be thought of as a large and unusual move. Second, it can be seen from Column 2 of Table 1 that, although racial dummy variables enter with well-determined coefficients, with both Black and Native Americans, for example, having coefficients of approximately -0.13, the size of the race effects in the equation is far smaller than that generated by income differences. This is a way of saying that, statistically, there is much more information in the income dummies than in the race dummies. This has not been the standard view -- it could be compared to that in Blanchflower and Oswald (2004) or an older psychology literature based on simple bivariate patterns -- but it seems potentially consistent with the finding of Stevenson and Wolfers (2008) that gender and racial differences in Americans' life-satisfaction have declined through recent decades. Third, the contribution to the R-squared from income dummies is many multiples of that from race, age and gender dummies. Fourth, it will be seen later that the income-dummy coefficients correspond to large effects when examined against, for example, major life characteristics like being separated or unemployed.

The R-squared in column 1 of Table 1 is 0.077 whereas it is only 0.008 in column 2 of Table 1. An R-squared of 0.077 corresponds to a Pearson r coefficient of

0.28, which can be compared to the standard finding, in developed nations, of around 0.15 (pointed out in the review by Diener and Biswas-Diener 2002).

Columns 3 and 4 of Table 1 show that the income gradient of column 1 is only slightly affected by the inclusion of various sets of control variables. Perhaps most strikingly, there continues to be a difference of approximately 0.5 life satisfaction points, even in the long specification of column 4 of Table 1, between individuals in the highest income category and those in the lowest income category. This final column includes 50 state dummies, 11 month-of-interview dummies, and an extensive set of personal and demographic dummy variables. Comparing columns 1 and 4, the bivariate association between income and satisfaction is only marginally mediated by adjustment for approximately 80 other independent variables.

In these new American data there is some support for a U shape in life satisfaction through the life course[5]. This is visible from the age and age squared terms in columns 2, 3 and 4 of Table 1. Solving out the quadratic, the age at which minimum life satisfaction is reached is given in column 2 by age = 0.00222/0.00006 = 37 years old. Contrary to the American data in Easterlin (2006) and Glenn (2009), therefore, it is not necessary first to control for endogenous variables such as education or marriage or income. In column 3 of Table 1, the turning point is at age 43. In column 4, it is at age 40.

The other variables in column 4 of Table 1 have familiarly signed coefficients. Ceteris paribus, a college degree is associated with 0.1 extra life satisfaction points;

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[5] Because there are so many observations, it is of course possible to fit high-order polynomials, and there is evidence of unhappiness for a few years for people aged from 18+, and again among rather old people; we use a quadratic as an approximation and not because it does every justice to the details of the data set. It is simply that the paper's focus is elsewhere, and midlife is, in these data, characterized by low measured well-being. We acknowledge helpful discussions with Danny Blanchflower about these issues.

marriage when compared to being unmarried with 0.16 points; marital separation with -0.1 points; unemployment with -0.16 points; self-employment with 0.07 points.

Table 2 turns to life satisfaction patterns across the geography of the United States. Here the state-dummy coefficients are written out explicitly. Alabama is the omitted, base category. Thus the first state-dummy coefficient in column 1 of Table 2 can be interpreted as showing that satisfaction with life on average in Alaska is 0.0185 life satisfaction points above that in the base case of Alabama. Arizona residents have 0.0494 of extra life satisfaction on this cardinal scale; Arkansas is indistinguishable from Alabama; and so on across the listed states.

However, column 1 of Table 2 cannot tell us what life is truly like in each state of the union. Rather, it gives a measure of the average well-being of the typical resident of that state. Because states vary widely in the nature of their inhabitants, a more natural inquiry is to examine the coefficients on state dummies after controlling for personal and demographic features of the populations of each. This is what the later columns of Table 2 do.

Arguably the most interesting column of Table 2 is the fourth. In column 4, we have adjusted for all the non-financial features of individuals. This may appear strange, but there is an important reason not to hold constant people's income in statistical work of this sort. It is that if someone leaves West Virginia to live in California they are likely to earn a larger nominal salary, but other factors, such as house prices and traffic congestion, will tend to be worse. Hence if we control in a well-being regression equation for their level of income, the structure of the state dummies in the equation will tell us about the remaining intrinsic state disamenities for which compensating higher pay must be offered. The purpose of the exercise here is instead to understand the net benefits or losses from being a citizen of the state.

How much do life satisfaction levels then vary from state to state? The answer is, by some standards, fairly widely. The notably poor life-satisfaction states are then California (-0.0367), Illinois (-0.0372), Indiana (-0.0689), Kentucky (-.00631), Massachusetts (-0.0458), Michigan (-0.0559), Missouri (-0.0606), Nebraska (-0.0479), New York (-0.0570), Ohio (-0.0588), Pennsylvania (-0.0632), Rhode Island (-0.0419), and West Virginia (-0.0599). The high-satisfaction states are DC (0.0242), Florida (0.0174), Hawaii (0.0454), and Louisiana (0.0499). The standard errors correspond in each case to a test of the null hypothesis of zero on the coefficient. It should not be presumed that there is a statistically significant difference between each of the states within these two low-satisfaction and high-satisfaction groups. The null of well-being equality in Indiana and Kentucky, for example, cannot be rejected.

Tables 3 and 4 present equivalent results. In these cases, however, we switch to a dependent variable that measures mental ill-health. This is the number of days, in the last 30 days, that people feel they suffered from poor mental health.[6] The median answer is zero, and by the nature of the data it is not possible for those with good mental health to distinguish themselves from those with sound mental health. For this reason, we use a Tobit estimator, but the results are not sensitive to this choice.

The first thing noticeable in column 1 of Table 3 is the strong income gradient. The difference between the lowest and highest income categories is a coefficient of -12.68 days of poor mental health. This column of Table 3 is closely reminiscent of the earlier life satisfaction results. Again, there is marked monotonicity in the income dummy variables. This gradient is suggestive of, but

[6] Moriarty et. al. (2009) construct a variable based on the same question in the BRFSS, the number of individuals with “frequent mental distress”, defined as having at least 14 days of poor mental health in the past month. Although a different criterion than we use, and closer to a measure of severe mental illness, our rankings of state-level mental well-being are fairly similar to theirs.

stronger than, some equivalent studies on physical health (such as, recently, Pham-Kanter 2009).

The age structure in these mental-health equations is qualitatively consistent with that found in the earlier life satisfaction specifications. There is now a hill-shaped relationship between mental ill-being and age. In columns 2, 3 and 4 of Table 3, the turning point occurs at ages 28, 34, and 35. These are at slightly younger ages than in Table 1. Other variables enter in qualitatively predictable ways. For example, unemployment is associated with 3 extra days of poor mental health; a college degree with one and a half fewer days; marital separation with 4 extra days.

With a few notable exceptions, there is much agreement between the qualitative structure of these American life satisfaction and mental distress equations. A natural comparison is between column 4 of Table 1 and column 4 of Table 3. The main differences in the coefficient signs are for Asian, Native American, female, and student. Most variables enter with equivalent effects for each of the two kinds of dependent variable. This finding is against the spirit of Huppert and Whittington's (2003) argument that positive and negative 'affect' are strongly different in character.

Table 4 moves to regressions showing the state-by-state pattern in the number of days of poor mental health. The stand-out case in column 4 of Table 4 is California, with the worst mental health across the US states (a coefficient of 0.599). The best mental health, i.e. states with the fewest number of poor mental health days, is found in Iowa, Louisiana, Nebraska, the two Dakotas, and Tennessee. Another method is to examine which states are found in the lowest (and highest) quartiles on both measures, namely, on the life-satisfaction scores and the mental-distress-days scores. Doing so yields the follow list of states in the lowest quartile of well-being on both measures: *California, Kentucky, Michigan, Ohio, West Virginia, and Missouri*.

The states in the highest quartile of well-being on both measures: *Louisiana, D.C., Alaska, Tennessee, and Colorado*.

How else might these two forms of well-being measure be combined? Figures 1 to 4 set out various checks and suggest that the two kinds are here, as might be expected, providing reinforcing information. Satisfied U.S. states are noticeably also the mentally healthy ones. To our knowledge, this result is a new one.

A final issue that deserves consideration is whether the stark results on the states of California (with poor mental health) and Louisiana (with high well-being overall) are caused by the later years in this sample of four years. Might it be, say, that the credit crunch that had hit California by 2007/8, or the aftermath of Hurricane Katrina in Louisiana in the latter part of 2005, somehow led to extreme values in those state dummies? To check this, we re-ran the key regressions equations for the early year of 2005 data alone. The results for California and Louisiana, for example, were almost identical to those in the full sample. Hence, crucially, the patterns documented in this paper are not merely the product of the last year or two of data.

As a final and important check that there is not some fundamental problem with the mental health data in BRFSS, Figure 8 reveals a reassuringly similar state pattern, for the interesting case of young people (these other data are necessarily regression-uncorrected but that should be less important among non-working young people), from the National Survey on Drug Use and Health.

These differences in well-being across states are not minor. In cardinalized terms, they correspond to up to 0.2 life-satisfaction points, which is similar in size to the ceteris paribus cross-sectional effect of marital separation or unemployment. The economist's natural null hypothesis of equality of well-being across areas is, *in its* *strict version*, rejected by the data. Interestingly, it is not different states' material riches that determine their position in this spatial well-being ordering.

Figure 5 illustrates that fact. There exists no statistically significant correlation, although a best-fitting line would have a very small positive gradient, between state well-being and state GDP per capita. By contrast, and conceptually a different form of comparison, Figure 6 shows that if we control for household income -- the micro equations are not given in the tables but are available upon request -- then this gradient is negative.[7] This, *in a weaker version*, is what compensating-differentials theory would predict. It should be emphasized that the paper's results do not merely tell us the obvious fact that factors like the climate or air cleanliness or beauty are better in some places than in others. The intellectual issue is why the plusses and minuses from innate state differences, such as sunshine hours or beautiful lakes, are not eroded -- indeed right back up to the point where all areas provide the same net utility. Even after adjusting for individuals' backgrounds and characteristics, there remain significant unexplained differences[8] state-by-state in Americans' well-being.

5. Conclusions

Using the BRFSS survey of the United States, this paper examines information on 1.3 million randomly sampled US citizens for the years 2005 to 2008. It uses data on life-satisfaction scores and on people's recorded numbers of days in poor mental health. The econometric structure of these two kinds of well-being regression equations is similar, although, as noted in the text, not literally identical.

[7] This result is potentially consistent with the fixed-effects 'relative income concern' finding in Blanchflower and Oswald (2004) and Luttmer (2005). Ours, however, is naturally thought of as a correlation between the state fixed effects and other characteristics. Figure 7 is a variant and corroborative check.

[8] In current work we are exploring the ideas in Putnam (2000).

Some US states exhibit low levels of mental well-being, while relatively high levels are found among others. These differences are not quantitatively minor. Particularly notable in the data is, for example, the unusually happy state of Louisiana[9]. In contrast, and against some common perceptions, Californians are not happier than the inhabitants of other states (consistent with the data on college students studied in Schkade and Kahneman 1998). In fact, we show that they lie well below the mental well-being of people living in the majority of the United States.

Strikingly, these BRFSS data reveal that there is no correlation between U.S. states' mental well-being and their GDP per capita. Correcting for people's incomes, satisfaction with life is low in the rich states. Our results are consistent with a weak, but clearly not a strong, version of the arbitrage theory that areas should in equilibrium provide equal utility across space. Unlike informal quality-of-life rankings of the US states (such as Rampell, NY Times 2009 or Thompson Healthcare 2007), which primarily reveal the types of individuals who live in a place, and produce rather different rankings from ours, this paper adjusts for the nature of the citizens in the state.

Although, for completeness, we present a variety of regression-equation specifications, the most natural ones to focus on are those in the final columns of Tables 2 and 4. These specifications control for the detailed demographic backgrounds of individuals, but not for their incomes.[10] This is because an aim of the

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[9] Because we were initially surprised to find Louisiana do so well in these rankings, we checked for any corroborative evidence in the psychiatric literature. We discovered that Louisianan adolescent mental health, as measured by SAMHSA, Office of Applied Studies, National Survey on Drug Use and Health 2004-5, is the best of all the states in the USA. See the notes to Figure 8.

[10] For completeness, Figure A1 in the appendix reports a state cross-section plot of adjusted life satisfaction against fully-adjusted life satisfaction (controlling for personal household income), and there remains a strong positive correlation.

paper is to inquire into the overall well-being -- not an income-held-constant level of utility[11] -- that is provided in a geographical area.

Apart from our cross-state findings, there is empirical support for a far stronger income gradient than promulgated in the psychology literature. This result is in the same spirit as the argument of Deaton (2008) on international cross-section data. It might seem natural, for economists, to expect a powerful connection between income and happiness, but a recent review of the evidence in the psychology literature, for example, argues: “Within most economically developed nations, richer people are only slightly happier than most others” (Diener and Biswas-Diener, 2002). Our empirical results for individuals in the United States do not greatly accord with this view. But they do agree with such a view, or an even stronger version of it, for the U.S. states themselves. Whether there are intellectual connections between the lack of a correlation in Figure 5 and the famous Easterlin Paradox (1974, 2003) remains to be understood, and, importantly, the observed patterns in U.S. state-by-state well-being demand explanation.

11 In practice, income plainly will typically not hold constant when, say, a college graduate moves from San Francisco to Vermont.

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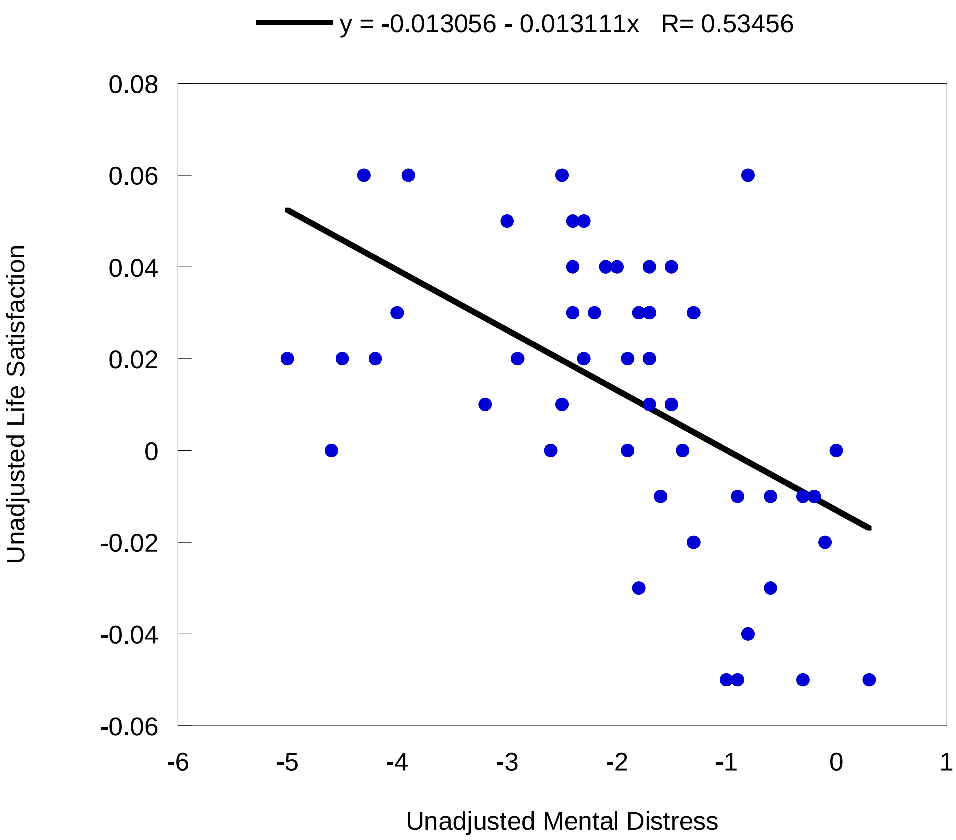
Figure 1

The Inverse Correlation Between Life Satisfaction and Mental Distress Days across the 51 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



Each dot is a state. The correlation is significant at 1% on a two-tailed test. This figure plots state dummy coefficients from a life-satisfaction equation against state dummy coefficients from a # mental-distress-days equation. In each equation, the regression controls only for year dummies and month of interview dummies. Life satisfaction is coded for each individual from 4 (very satisfied) to 1 (very dissatisfied). Mental distress days are coded from zero (no days) up to 30 (every day in the last month). The bottom right hand observation is Kentucky. Question wordings in the BRFSS questionnaire are:

Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?

(76–77)

In general, how satisfied are you with your life?

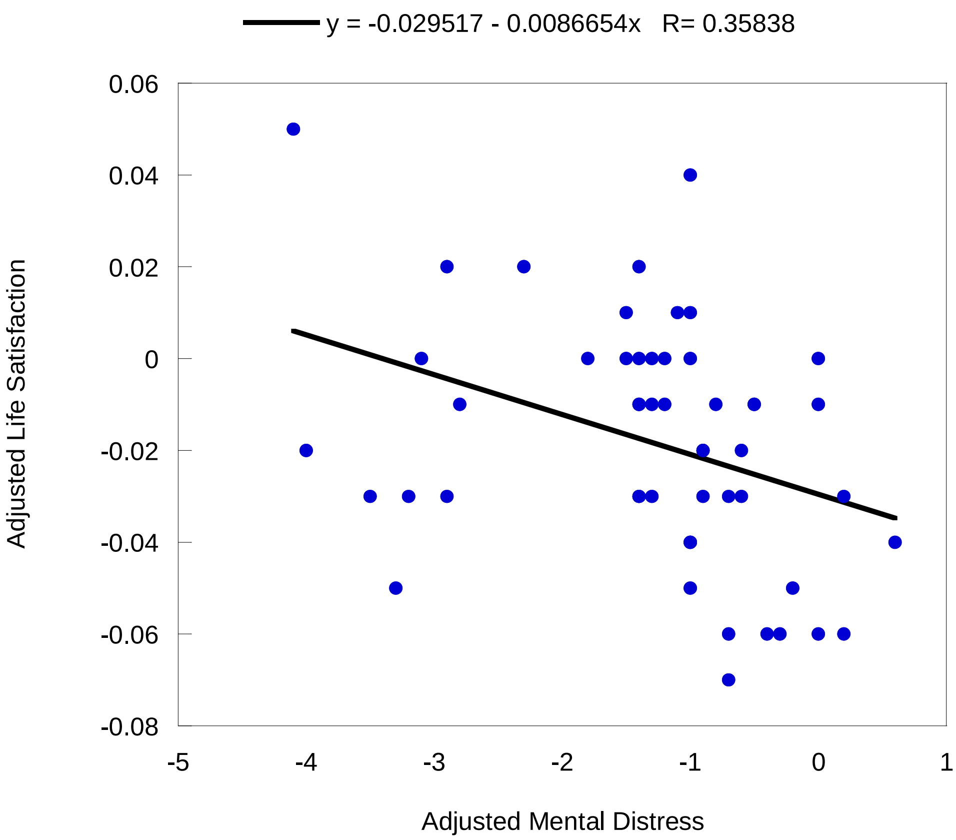
(206)

1 Very satisfied
2 Satisfied
3 Dissatisfied
4 Very dissatisfied

Figure 2

The Inverse Correlation Between (Regression-Adjusted) Life Satisfaction and (Regression-Adjusted) Mental Distress Days across the 51 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



Each dot is a state. The correlation is significant at 1% on a two-tailed test. This figure plots state dummy coefficients from a life-satisfaction equation against state dummy coefficients from a # mental-distress-days equation. In each equation, the regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also includes year dummies and month of interview dummies. Life satisfaction is coded for each individual from 4 (very satisfied) to 1 (very dissatisfied). Mental distress days are coded from zero (no days) up to 30 (every day in the last month). The upper left hand observation is Louisiana. The right hand observation with the highest level of mental distress is California. Question wordings in the BRFSS questionnaire are:

Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?

(76–77)

In general, how satisfied are you with your life?

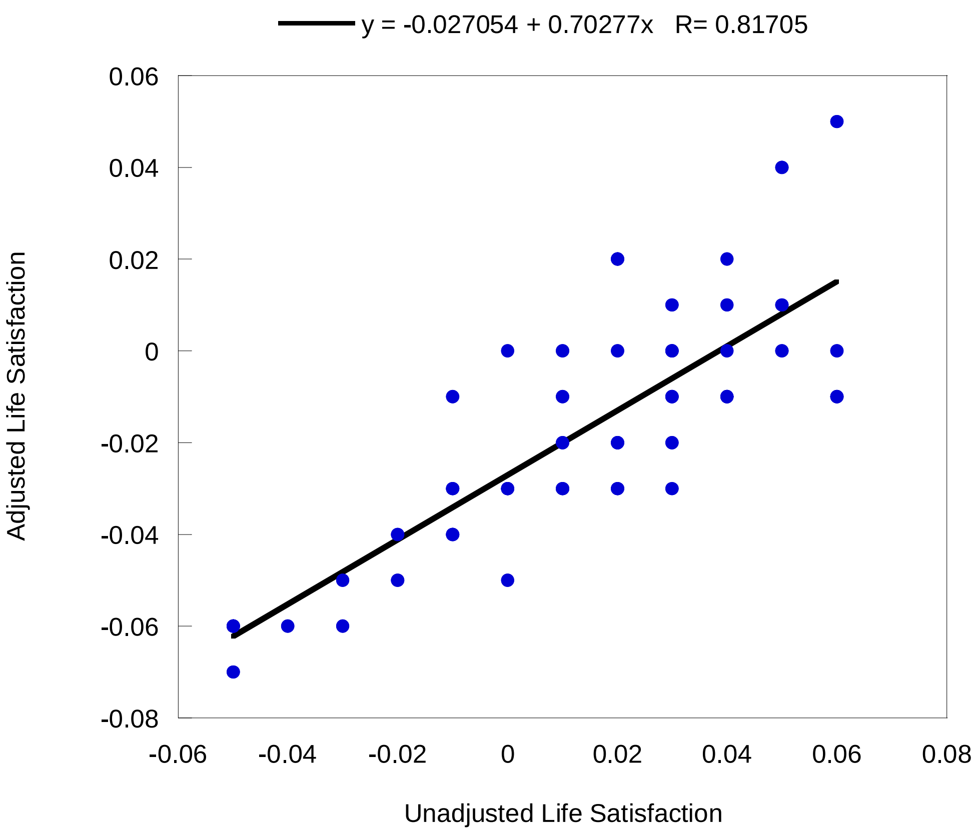
(206)

1 Very satisfied
2 Satisfied
3 Dissatisfied
4 Very dissatisfied

Figure 3

The Correlation Between Adjusted Life Satisfaction and Unadjusted Life Satisfaction across the 51 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.

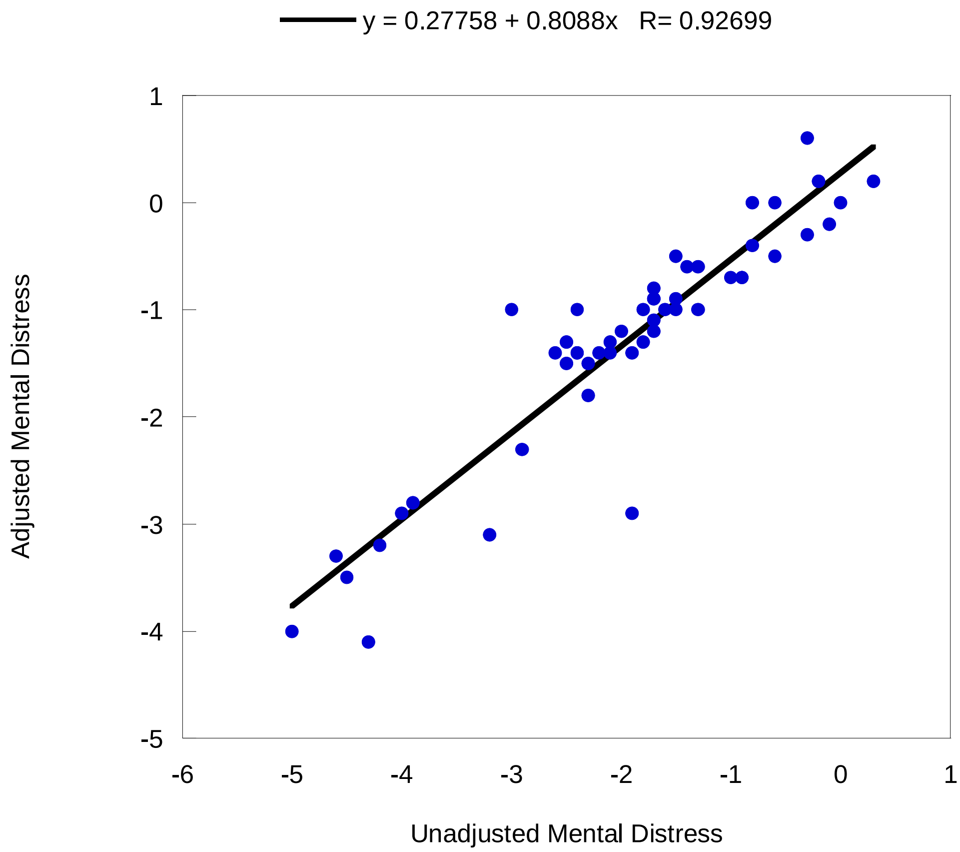


Each dot is a state. In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies. In unadjusted data, there are only year dummies and month-of-interview dummies.

Figure 4

The Correlation Between Adjusted Mental Distress Days and Unadjusted Mental Distress Days across the 51 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.

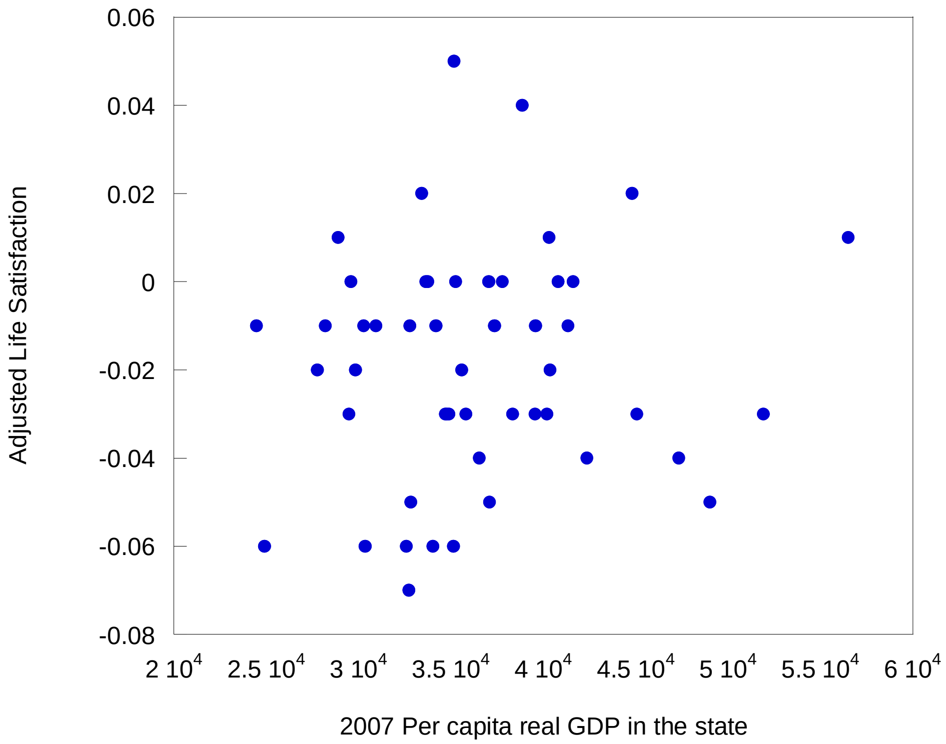


Each dot is a state. In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies. In unadjusted data, there are only year dummies and month-of-interview dummies.

Figure 5

The Absence of Correlation Between Adjusted Life Satisfaction and GDP Per Capita across 50 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



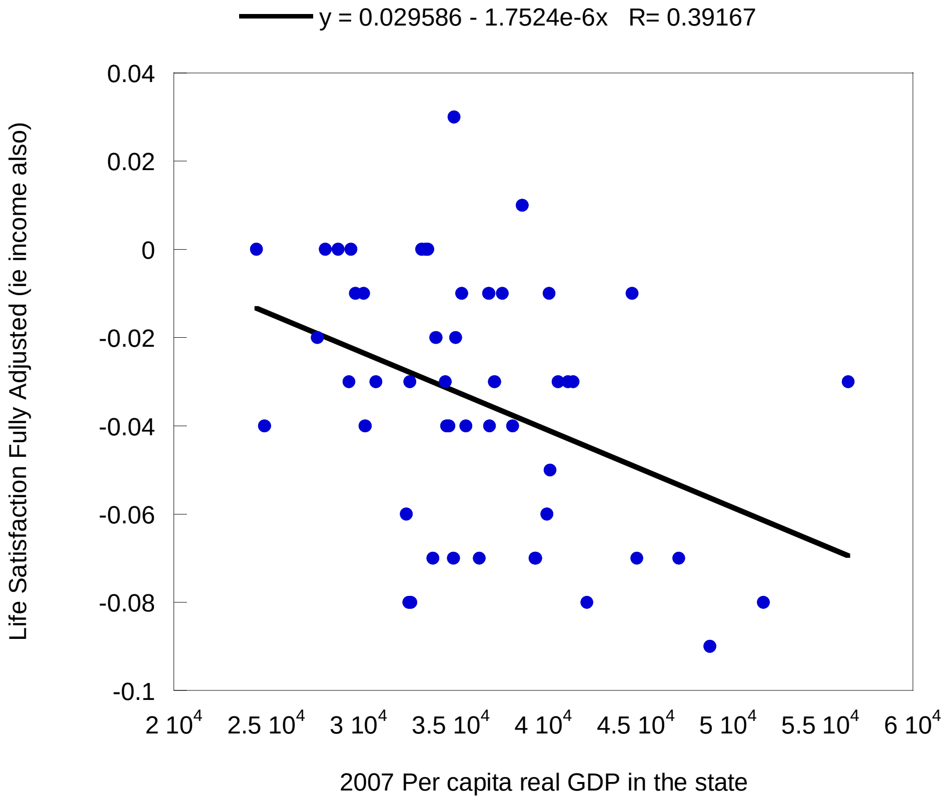
Each dot is a state. Washington DC is omitted (for compositional reasons, its GDP per head is hard to compare with that of other states). GDP data are for 2007 and are from the standard Bureau of Economic Analysis source. Pearson's r here is positive but below 0.1.

In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

Figure 6

The Inverse Correlation Between Fully Adjusted Life Satisfaction and GDP Per Capita across 50 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



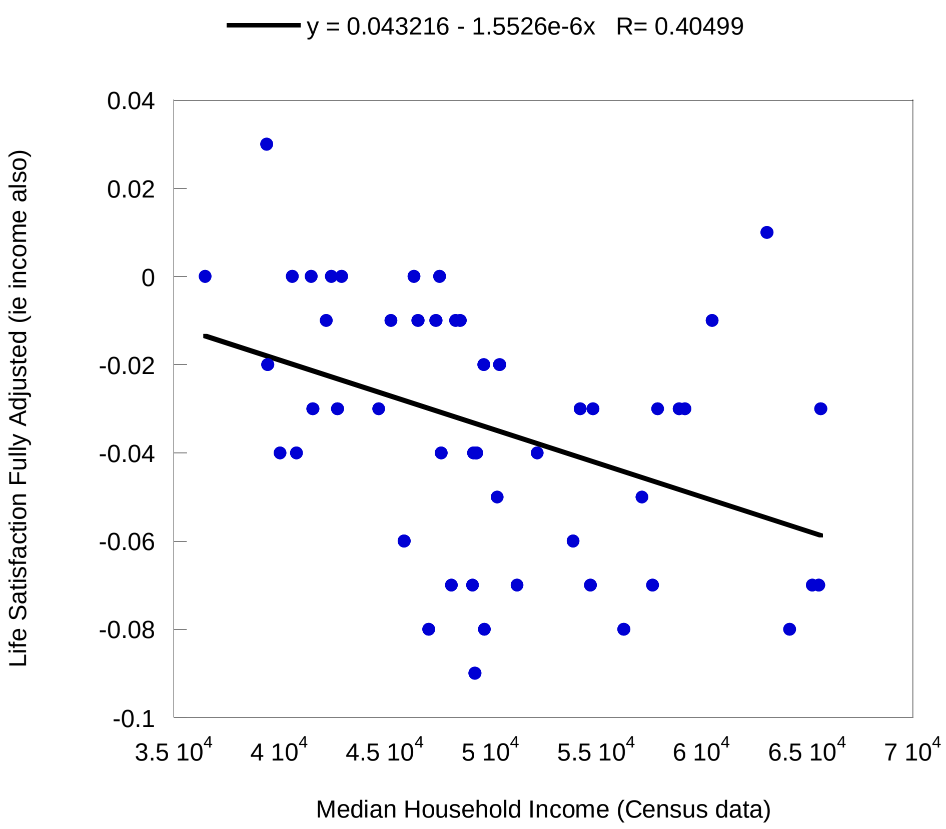
Each dot is a state. The correlation is significant at 1% on a two-tailed test. Washington DC is omitted (for compositional reasons, its GDP per head is hard to compare with that of other states). GDP data are for 2007 and are from the standard Bureau of Economic Analysis source.

In fully adjusted data, there are regression controls for household income as well as the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

Figure 7

The Inverse Correlation Between Fully Adjusted Life Satisfaction and Median Household Income across 51 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



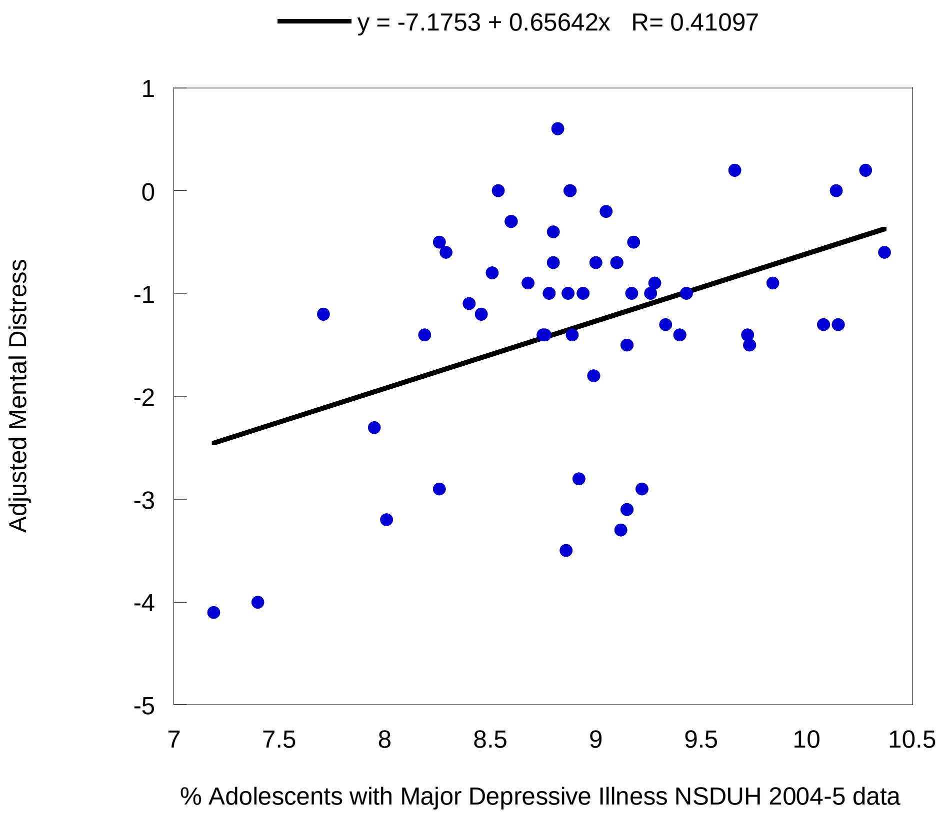
Each dot is a state. The correlation is significant at 1% on a two-tailed test. Household income data are constructed from the CPS and Census. 2006-2008 Annual Supplements.

In fully adjusted data, there are regression controls for household income as well as the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

Figure 8

The Correlation Between Adjusted Mental Distress and the Proportion of Youths Aged 12-17 with a Major Depressive Episode in the Past Year in NSDUH Data

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



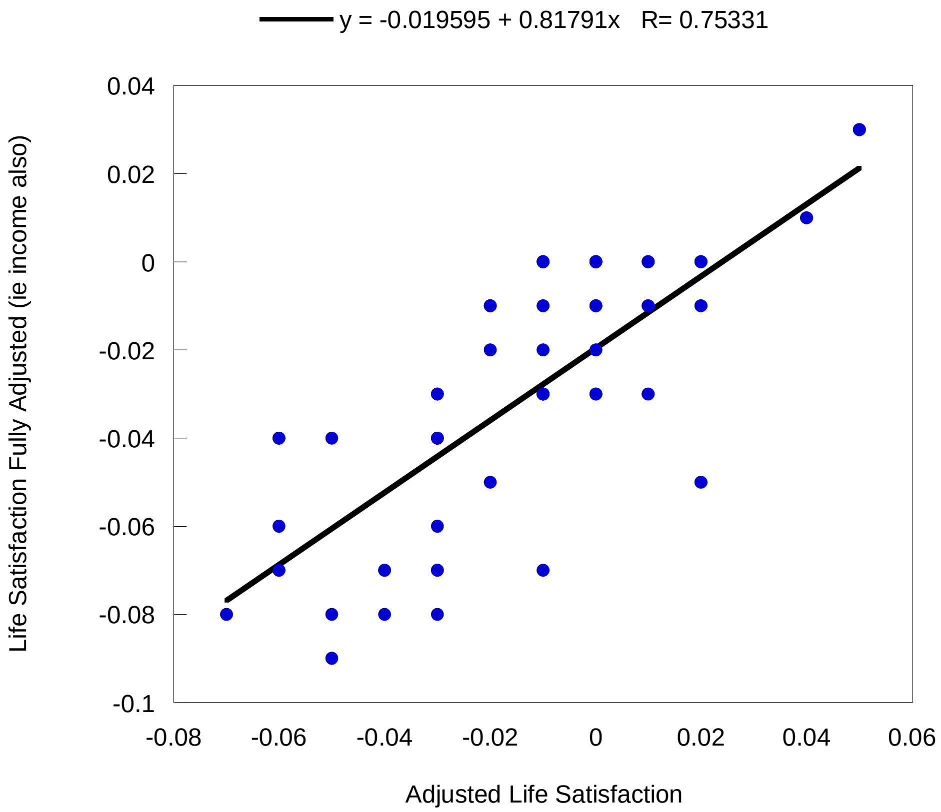
Each dot is a state. The correlation is significant at 1% on a two-tailed test. The data on rates of adolescent depression come from Mental Health America and the SAMHSA, Office of Applied Studies, National Survey on Drug Use and Health 2004-5. The bottom left hand observation is Louisiana.

In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

Appendix Figure A1

The Correlation Between Adjusted Life Satisfaction and Fully Adjusted Life Satisfaction (i.e. also for individual households' income levels) across 51 States of the USA

BRFSS Data: 2005-8. Sample size = 1.3 million approx.



Each dot is a state.

In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies. Fully adjusted life satisfaction also controls for household income.

Table 1. Life Satisfaction Equations: BRFSS Pooled Data 2005-2008

VARIABLES	(1)	(2)	(3)	(4)
Income 10-15K	0.116**	…	0.0914**	0.0649**
	(0.00330)		(0.00333)	(0.00331)
Income 15-20K	0.202**	…	0.184**	0.135**
	(0.00311)		(0.00315)	(0.00314)
Income 20-25K	0.265**	…	0.256**	0.185**
	(0.00298)		(0.00302)	(0.00304)
Income 25-35K	0.338**	…	0.341**	0.249**
	(0.00284)		(0.00288)	(0.00294)
Income 35-50K	0.413**	…	0.437**	0.317**
	(0.00275)		(0.00281)	(0.00292)
Income 50-75K	0.492**	…	0.535**	0.390**
	(0.00273)		(0.00281)	(0.00299)
Income >75K	0.607**	…	0.666**	0.487**
	(0.00263)		(0.00274)	(0.00302)
Age	…	-0.00222**	-0.0165**	-0.0145**
		(0.000196)	(0.000211)	(0.000233)
Age Squared	…	2.99e-05**	0.000191**	0.000153**
		(1.84e-06)	(2.01e-06)	(2.29e-06)
Black	…	-0.129**	-0.00226	0.0326**
		(0.00207)	(0.00215)	(0.00215)
Asian	…	-0.0329**	-0.0330**	-0.0542**
		(0.00430)	(0.00438)	(0.00434)
Hispanic	…	-0.0858**	0.0574**	0.0537**
		(0.00240)	(0.00250)	(0.00253)
Native American	…	-0.128**	-0.00339	0.0153**
		(0.00422)	(0.00429)	(0.00425)
Other Minority	…	-0.0583*	-0.0225	-0.0278
		(0.0287)	(0.0283)	(0.0280)
Female	…	-0.00374**	0.0361**	0.0391**
		(0.00110)	(0.00112)	(0.00116)
Some High School	…	…	…	-0.00398
				(0.00395)
High School	…	…	…	0.0365**
				(0.00351)
Some College	…	…	…	0.0364**
				(0.00358)
College	…	…	…	0.0977**
				(0.00362)
Married	…	…	…	0.165**
				(0.00191)

Divorced	…	…	…	-0.000826
				(0.00223)
Separated	…	…	…	-0.101**
				(0.00395)
Widowed	…	…	…	0.0365**
				(0.00260)
Partner	…	…	…	0.0517**
				(0.00377)
Self employed	…	…	…	0.0666**
				(0.00193)
Unemployed	…	…	…	-0.160**
				(0.00290)
Homemaker	…	…	…	0.0646**
				(0.00223)
Student	…	…	…	0.0827**
				(0.00440)
Retired	…	…	…	0.104**
				(0.00187)
Constant	2.986**	3.432**	3.283**	3.215**
	(0.00259)	(0.00686)	(0.00759)	(0.00856)
Observations	1249254	1385376	1216640	1213992
R-squared	0.077	0.008	0.093	0.115

Notes: Standard errors are in parentheses. * Significant at 5%, ** Significant at 1%
All regressions include state effects and controls for month and year of survey.
Life Satisfaction is measured on 1-4 scale; 1=very dissatisfied, 4=very satisfied.

Table 2. Life Satisfaction Equations: BRFSS Pooled Data 2005-2008

VARIABLES	(1)	(2)	(3)	(4)
Age	…	-0.00221**	-0.0135**	-0.0105**
		(0.000196)	(0.000205)	(0.000216)
Age Squared	…	2.99e-05**	0.000145**	0.000104**
		(1.84e-06)	(1.94e-06)	(2.11e-06)
Black	…	-0.129**	-0.0188**	-0.00994**
		(0.00207)	(0.00204)	(0.00204)
Asian	…	-0.0329**	-0.0768**	-0.0728**
		(0.00430)	(0.00417)	(0.00415)
Hispanic	…	-0.0858**	-0.00490*	-0.00237
		(0.00240)	(0.00240)	(0.00239)
Native American	…	-0.128**	-0.0453**	-0.0332**
		(0.00422)	(0.00409)	(0.00408)
Other Minority	…	-0.0583*	-0.0609*	-0.0569*
		(0.0287)	(0.0278)	(0.0277)
Female	…	-0.00372**	0.0208**	0.0207**
		(0.00110)	(0.00108)	(0.00111)
Some High School	…	…	0.0232**	0.0252**
			(0.00358)	(0.00357)
High School	…	…	0.128**	0.124**
			(0.00314)	(0.00313)
Some College	…	…	0.172**	0.165**
			(0.00318)	(0.00317)
College	…	…	0.296**	0.287**
			(0.00317)	(0.00317)
Married	…	…	0.277**	0.263**
			(0.00176)	(0.00177)
Divorced	…	…	-0.00870**	-0.0101**
			(0.00215)	(0.00215)
Separated	…	…	-0.125**	-0.123**
			(0.00382)	(0.00380)
Widowed	…	…	0.0538**	0.0469**
			(0.00244)	(0.00244)
Partner	…	…	0.0931**	0.0891**
			(0.00365)	(0.00364)
Self employed	…		…	0.0738**
				(0.00187)
Unemployed	…		…	-0.235**
				(0.00271)
Homemaker	…		…	0.0532**

				(0.00206)
Student	…		…	0.0624**
				(0.00405)
Retired	…		…	0.0838**
				(0.00174)
Alaska	0.0185*	0.0194*	0.0130	0.0186*
	(0.00789)	(0.00804)	(0.00778)	(0.00775)
Arizona	0.0494**	0.0387**	0.0134*	0.0101
	(0.00647)	(0.00655)	(0.00634)	(0.00631)
Arkansas	0.00995	-0.00899	-0.0192**	-0.0202**
	(0.00632)	(0.00636)	(0.00615)	(0.00613)
California	-0.0104	-0.0151*	-0.0367**	-0.0369**
	(0.00599)	(0.00609)	(0.00590)	(0.00587)
Colorado	0.0595**	0.0413**	0.00366	0.00246
	(0.00573)	(0.00578)	(0.00560)	(0.00557)
Connecticut	0.0124*	-0.00763	-0.0359**	-0.0315**
	(0.00606)	(0.00609)	(0.00590)	(0.00588)
Delaware	0.0455**	0.0302**	0.0103	0.00807
	(0.00680)	(0.00685)	(0.00662)	(0.00659)
District of Columbia	0.0254**	0.0515**	0.0224**	0.0216**
	(0.00694)	(0.00700)	(0.00680)	(0.00677)
Florida	0.0406**	0.0237**	0.0174**	0.0165**
	(0.00521)	(0.00524)	(0.00507)	(0.00505)
Georgia	0.0270**	0.0216**	0.000865	0.000475
	(0.00604)	(0.00606)	(0.00586)	(0.00584)
Hawaii	0.0531**	0.0549**	0.0454**	0.0400**
	(0.00607)	(0.00686)	(0.00664)	(0.00661)
Idaho	0.0303**	0.00255	-0.0186**	-0.0222**
	(0.00637)	(0.00642)	(0.00621)	(0.00618)
Illinois	0.00469	-0.0109	-0.0372**	-0.0349**
	(0.00640)	(0.00642)	(0.00622)	(0.00619)
Indiana	-0.0486**	-0.0671**	-0.0689**	-0.0662**
	(0.00627)	(0.00630)	(0.00610)	(0.00607)
Iowa	0.0239**	-0.00887	-0.0276**	-0.0285**
	(0.00635)	(0.00638)	(0.00617)	(0.00614)
Kansas	0.0263**	-0.000838	-0.0320**	-0.0326**
	(0.00576)	(0.00579)	(0.00560)	(0.00558)
Kentucky	-0.0522**	-0.0822**	-0.0631**	-0.0642**
	(0.00605)	(0.00607)	(0.00588)	(0.00585)
Louisiana	0.0618**	0.0586**	0.0499**	0.0479**
	(0.00627)	(0.00629)	(0.00608)	(0.00605)
Maine	0.0264**	-0.00602	-0.0137*	-0.0117
	(0.00635)	(0.00639)	(0.00618)	(0.00615)
Maryland	0.0356**	0.0243**	-0.0123*	-0.0128*
	(0.00573)	(0.00575)	(0.00557)	(0.00555)
Massachusetts	-0.0221**	-0.0415**	-0.0458**	-0.0397**

	(0.00527)	(0.00530)	(0.00514)	(0.00511)
Michigan	-0.0213**	-0.0369**	-0.0559**	-0.0545**
	(0.00574)	(0.00577)	(0.00559)	(0.00556)
Minnesota	0.0553**	0.0238**	-0.00653	-0.00711
	(0.00680)	(0.00682)	(0.00660)	(0.00657)
Mississippi	-0.00901	-0.00441	-0.00822	-0.00687
	(0.00607)	(0.00608)	(0.00588)	(0.00585)
Missouri	-0.0417**	-0.0633**	-0.0606**	-0.0602**
	(0.00642)	(0.00645)	(0.00624)	(0.00621)
Montana	0.0345**	0.00957	-0.00879	-0.0120*
	(0.00622)	(0.00627)	(0.00606)	(0.00604)
Nebraska	0.00442	-0.0280**	-0.0479**	-0.0486**
	(0.00553)	(0.00557)	(0.00539)	(0.00536)
Nevada	-0.00645	-0.0209**	-0.0263**	-0.0272**
	(0.00690)	(0.00709)	(0.00686)	(0.00683)
New Hampshire	0.0397**	0.00668	-0.0141*	-0.0123*
	(0.00616)	(0.00620)	(0.00600)	(0.00597)
New Jersey	0.00324	-0.0107	-0.0353**	-0.0312**
	(0.00553)	(0.00556)	(0.00538)	(0.00536)
New Mexico	0.00792	0.0128*	-0.0103	-0.0128*
	(0.00615)	(0.00626)	(0.00606)	(0.00603)
New York	-0.0286**	-0.0435**	-0.0570**	-0.0549**
	(0.00602)	(0.00607)	(0.00588)	(0.00585)
North Carolina	0.0166**	0.00749	-0.00399	-0.00414
	(0.00524)	(0.00525)	(0.00508)	(0.00506)
North Dakota	0.0230**	-0.00767	-0.0261**	-0.0273**
	(0.00660)	(0.00663)	(0.00642)	(0.00639)
Ohio	-0.0324**	-0.0503**	-0.0588**	-0.0563**
	(0.00568)	(0.00570)	(0.00552)	(0.00549)
Oklahoma	-0.00972	-0.0201**	-0.0291**	-0.0305**
	(0.00571)	(0.00580)	(0.00561)	(0.00559)
Oregon	0.0128*	-0.0148*	-0.0329**	-0.0342**
	(0.00606)	(0.00612)	(0.00592)	(0.00590)
Pennsylvania	-0.0512**	-0.0712**	-0.0632**	-0.0608**
	(0.00538)	(0.00540)	(0.00523)	(0.00520)
Rhode Island	-0.0116	-0.0352**	-0.0419**	-0.0361**
	(0.00671)	(0.00675)	(0.00653)	(0.00650)
South Carolina	0.0335**	0.0290**	0.0120*	0.0144**
	(0.00565)	(0.00567)	(0.00549)	(0.00546)
South Dakota	0.0214**	-0.00486	-0.0216**	-0.0230**
	(0.00603)	(0.00607)	(0.00587)	(0.00585)
Tennessee	0.0104	-0.0127	0.00536	0.00392
	(0.00654)	(0.00656)	(0.00634)	(0.00631)
Texas	0.0309**	0.0294**	0.00378	0.00273
	(0.00559)	(0.00566)	(0.00548)	(0.00545)
Utah	0.0630**	0.0363**	-0.0110	-0.0140*

	(0.00639)	(0.00643)	(0.00622)	(0.00620)
Vermont	0.0378**	0.00541	-0.0111	-0.0111
	(0.00601)	(0.00605)	(0.00586)	(0.00583)
Virginia	0.0386**	0.0265**	0.00182	0.000431
	(0.00630)	(0.00634)	(0.00613)	(0.00611)
Washington	0.0218**	-0.00308	-0.0252**	-0.0256**
	(0.00502)	(0.00507)	(0.00491)	(0.00489)
West Virginia	-0.0514**	-0.0844**	-0.0599**	-0.0601**
	(0.00683)	(0.00688)	(0.00665)	(0.00662)
Wisconsin	0.000355	-0.0210**	-0.0293**	-0.0265**
	(0.00622)	(0.00624)	(0.00604)	(0.00601)
Wyoming	0.0551**	0.0264**	0.00496	0.00142
	(0.00618)	(0.00622)	(0.00602)	(0.00600)
Constant	3.363**	3.430**	3.316**	3.278**
	(0.00500)	(0.00707)	(0.00751)	(0.00768)
Observations	1423955	1385376	1380524	1380524
R-squared	0.003	0.008	0.074	0.083

Notes: Standard errors are in parentheses. * Significant at 5%, ** Significant at 1%
All regressions include controls for month and year of survey.
Life Satisfaction is measured on 1-4 scale; 1=very dissatisfied, 4=very satisfied.

Table 3. Mental Distress Equations: BRFSS Pooled Data 2005-2008

Tobit Regressions Censored at Zero

VARIABLES	(1)	(2)	(3)	(4)
Income 10-15K	-4.003**	…	-2.665**	-2.137**
	(0.102)		(0.102)	(0.102)
Income 15-20K	-6.230**	…	-5.239**	-4.387**
	(0.0969)		(0.0972)	(0.0977)
Income 20-25K	-7.675**	…	-7.018**	-5.801**
	(0.0929)		(0.0934)	(0.0948)
Income 25-35K	-9.512**	…	-9.242**	-7.715**
	(0.0889)		(0.0896)	(0.0922)
Income 35-50K	-10.27**	…	-10.90**	-9.027**
	(0.0859)		(0.0871)	(0.0916)
Income 50-75K	-11.01**	…	-12.45**	-10.29**
	(0.0855)		(0.0874)	(0.0940)
Income >75K	-12.68**	…	-14.54**	-11.97**
	(0.0824)		(0.0853)	(0.0953)
Age	…	0.238**	0.490**	0.403**
		(0.00660)	(0.00707)	(0.00790)
Age Squared	…	-0.00430**	-0.00712**	-0.00580**
		(6.36e-05)	(6.91e-05)	(8.00e-05)
Black	…	0.662**	-2.059**	-2.520**
		(0.0678)	(0.0698)	(0.0702)
Asian	…	-3.945**	-3.710**	-3.465**
		(0.148)	(0.149)	(0.149)
Hispanic	…	-1.099**	-3.812**	-3.937**
		(0.0791)	(0.0818)	(0.0836)
Native American	…	3.761**	1.155**	0.793**
		(0.134)	(0.135)	(0.135)
Other Minority	…	0.734	-0.0181	0.0591
		(0.875)	(0.872)	(0.866)
Female	…	4.838**	4.086**	3.997**
		(0.0381)	(0.0383)	(0.0397)
Some High School	…	…	…	0.664**
				(0.130)
High School	…	…	…	-1.179**
				(0.117)
Some College	…	…	…	-0.333**
				(0.119)
College	…	…	…	-1.432**
				(0.121)
Married	…	…	…	-1.005**
				(0.0621)

Divorced	…	…	…	1.071**
				(0.0715)
Separated	…	…	…	4.148**
				(0.120)
Widowed	…	…	…	0.303**
				(0.0876)
Partner	…	…	…	1.424**
				(0.118)
Self employed	…	…	…	-2.019**
				(0.0660)
Unemployed	…	…	…	3.115**
				(0.0884)
Homemaker	…	…	…	-1.382**
				(0.0730)
Student	…	…	…	0.614**
				(0.135)
Retired	…	…	…	-2.733**
				(0.0665)
Constant	1.529**	-9.937**	-4.142**	-3.406**
	(0.0804)	(0.227)	(0.247)	(0.281)
Observations	1276100	1420130	1242693	1239907

Notes: Standard errors are in parentheses. * Significant at 5%, ** Significant at 1%
All regressions include state effects and controls for month and year of survey. Dependent variable: number of poor mental health days

Table 4. Mental Distress Equations: BRFSS Pooled Data 2005-2008

Tobit Regressions Censored at Zero

VARIABLES	(1)	(2)	(3)	(4)
Age	…	0.238**	0.408**	0.348**
		(0.00660)	(0.00701)	(0.00746)
Age Squared	…	-0.00429**	-0.00610**	-0.00506**
		(6.36e-05)	(6.81e-05)	(7.49e-05)
Black	…	0.660**	-1.335**	-1.548**
		(0.0678)	(0.0680)	(0.0679)
Asian	…	-3.946**	-3.067**	-3.218**
		(0.148)	(0.146)	(0.145)
Hispanic	…	-1.101**	-2.890**	-2.914**
		(0.0791)	(0.0808)	(0.0805)
Native American	…	3.759**	2.156**	1.869**
		(0.134)	(0.132)	(0.132)
Other Minority	…	0.708	0.951	0.863
		(0.875)	(0.868)	(0.864)
Female	…	4.836**	4.451**	4.408**
		(0.0381)	(0.0379)	(0.0388)
Some High School	…	…	-0.111	-0.161
			(0.120)	(0.120)
High School	…	…	-3.705**	-3.587**
			(0.106)	(0.106)
Some College	…	…	-3.761**	-3.608**
			(0.108)	(0.108)
College	…	…	-6.342**	-6.065**
			(0.108)	(0.108)
Married	…	…	-3.992**	-3.498**
			(0.0578)	(0.0585)
Divorced	…	…	1.206**	1.322**
			(0.0702)	(0.0702)
Separated	…	…	4.743**	4.820**
			(0.118)	(0.118)
Widowed	…	…	-0.187*	0.124
			(0.0838)	(0.0838)
Partner	…	…	0.199	0.419**
			(0.116)	(0.116)
Self employed	…	…	…	-2.345**
				(0.0652)
Unemployed	…	…	…	4.920**
				(0.0842)
Homemaker	…	…	…	-1.365**

				(0.0694)
Student	…	…	…	1.204**
				(0.127)
Retired	…	…	…	-2.633**
				(0.0631)
Alaska	-1.914**	-3.147**	-2.926**	-2.995**
	(0.265)	(0.269)	(0.265)	(0.264)
Arizona	-2.454**	-1.629**	-1.119**	-1.009**
	(0.217)	(0.219)	(0.215)	(0.214)
Arkansas	-1.473**	-1.120**	-0.898**	-0.866**
	(0.211)	(0.212)	(0.208)	(0.207)
California	-0.295	0.191	0.570**	0.599**
	(0.196)	(0.198)	(0.195)	(0.195)
Colorado	-2.471**	-2.313**	-1.513**	-1.458**
	(0.191)	(0.192)	(0.189)	(0.188)
Connecticut	-2.494**	-1.887**	-1.241**	-1.341**
	(0.203)	(0.203)	(0.200)	(0.199)
Delaware	-1.534**	-1.492**	-1.036**	-0.951**
	(0.228)	(0.229)	(0.225)	(0.224)
District of Columbia	-2.867**	-3.062**	-2.299**	-2.260**
	(0.233)	(0.233)	(0.230)	(0.229)
Florida	-2.373**	-1.596**	-1.456**	-1.398**
	(0.174)	(0.174)	(0.171)	(0.170)
Georgia	-1.671**	-1.642**	-1.221**	-1.208**
	(0.202)	(0.201)	(0.198)	(0.197)
Hawaii	-3.032**	-1.508**	-1.163**	-0.961**
	(0.205)	(0.232)	(0.228)	(0.227)
Idaho	-1.285**	-1.166**	-0.756**	-0.641**
	(0.212)	(0.212)	(0.209)	(0.208)
Illinois	-1.420**	-1.132**	-0.516*	-0.574**
	(0.213)	(0.213)	(0.209)	(0.208)
Indiana	-0.869**	-0.801**	-0.686**	-0.741**
	(0.208)	(0.208)	(0.204)	(0.204)
Iowa	-4.252**	-3.776**	-3.262**	-3.239**
	(0.216)	(0.217)	(0.213)	(0.212)
Kansas	-4.042**	-3.621**	-2.915**	-2.881**
	(0.195)	(0.196)	(0.192)	(0.192)
Kentucky	0.333	0.542**	0.156	0.199
	(0.199)	(0.199)	(0.196)	(0.195)
Louisiana	-4.297**	-4.503**	-4.212**	-4.139**
	(0.215)	(0.215)	(0.211)	(0.210)
Maine	-1.774**	-1.471**	-1.253**	-1.280**
	(0.212)	(0.213)	(0.209)	(0.208)
Maryland	-1.746**	-1.597**	-0.829**	-0.788**
	(0.191)	(0.190)	(0.187)	(0.186)
Massachusetts	-1.312**	-0.977**	-0.824**	-0.966**

	(0.175)	(0.175)	(0.172)	(0.172)
Michigan	-0.967**	-0.686**	-0.208	-0.228
	(0.191)	(0.191)	(0.188)	(0.187)
Minnesota	-3.890**	-3.574**	-2.844**	-2.804**
	(0.233)	(0.232)	(0.228)	(0.227)
Mississippi	-0.650**	-0.585**	-0.517**	-0.532**
	(0.202)	(0.202)	(0.198)	(0.197)
Missouri	-0.786**	-0.424*	-0.411*	-0.409*
	(0.213)	(0.213)	(0.209)	(0.208)
Montana	-2.221**	-2.016**	-1.553**	-1.443**
	(0.208)	(0.209)	(0.206)	(0.205)
Nebraska	-4.556**	-3.929**	-3.386**	-3.349**
	(0.187)	(0.188)	(0.184)	(0.184)
Nevada	-0.225	0.0707	0.212	0.271
	(0.227)	(0.233)	(0.229)	(0.228)
New Hampshire	-2.184**	-1.850**	-1.411**	-1.437**
	(0.206)	(0.206)	(0.203)	(0.202)
New Jersey	-2.636**	-1.971**	-1.341**	-1.418**
	(0.184)	(0.184)	(0.181)	(0.181)
New Mexico	-1.480**	-1.111**	-0.565**	-0.506*
	(0.205)	(0.207)	(0.204)	(0.203)
New York	-1.826**	-1.397**	-1.006**	-1.038**
	(0.200)	(0.201)	(0.198)	(0.197)
North Carolina	-2.334**	-2.100**	-1.861**	-1.849**
	(0.175)	(0.175)	(0.172)	(0.171)
North Dakota	-4.493**	-4.091**	-3.556**	-3.510**
	(0.226)	(0.226)	(0.222)	(0.221)
Ohio	-0.602**	-0.223	0.0314	-0.0314
	(0.188)	(0.188)	(0.185)	(0.184)
Oklahoma	-0.894**	-0.944**	-0.767**	-0.725**
	(0.190)	(0.193)	(0.189)	(0.189)
Oregon	-1.735**	-1.267**	-0.927**	-0.870**
	(0.202)	(0.204)	(0.200)	(0.200)
Pennsylvania	-1.034**	-0.687**	-0.688**	-0.753**
	(0.179)	(0.178)	(0.175)	(0.175)
Rhode Island	-1.577**	-1.125**	-0.911**	-1.035**
	(0.223)	(0.224)	(0.220)	(0.219)
South Carolina	-1.734**	-1.448**	-1.126**	-1.168**
	(0.189)	(0.189)	(0.185)	(0.185)
South Dakota	-5.017**	-4.650**	-4.158**	-4.088**
	(0.207)	(0.207)	(0.204)	(0.203)
Tennessee	-3.179**	-2.821**	-3.128**	-3.073**
	(0.223)	(0.222)	(0.219)	(0.218)
Texas	-2.444**	-1.937**	-1.454**	-1.413**
	(0.187)	(0.188)	(0.185)	(0.185)
Utah	-0.803**	-0.905**	0.00433	0.115

	(0.212)	(0.212)	(0.209)	(0.208)
Vermont	-2.012**	-1.583**	-1.183**	-1.164**
	(0.201)	(0.202)	(0.198)	(0.198)
Virginia	-2.085**	-1.867**	-1.345**	-1.302**
	(0.211)	(0.212)	(0.208)	(0.207)
Washington	-1.731**	-1.368**	-0.933**	-0.901**
	(0.167)	(0.168)	(0.165)	(0.165)
West Virginia	-0.346	0.105	-0.310	-0.309
	(0.229)	(0.230)	(0.226)	(0.225)
Wisconsin	-1.864**	-1.661**	-1.364**	-1.435**
	(0.206)	(0.206)	(0.202)	(0.202)
Wyoming	-2.301**	-2.039**	-1.543**	-1.421**
	(0.207)	(0.208)	(0.204)	(0.204)
Constant	-6.644**	-10.11**	-7.178**	-6.841**
	(0.167)	(0.234)	(0.252)	(0.259)
Observations	1460011	1420130	1413997	1413885

Notes: Standard errors are in parentheses. * Significant at 5%, ** Significant at 1%
All regressions include controls for month and year of survey. Dependent variable: number of poor mental health days

Appendix

Table A1: Summary Statistics

Variable	Mean	Std. Dev.
Life Satisfaction (1-4 Scale)	3.386	0.629
Poor Mental Health Days Per Month	3.400	7.688
Income 10-15K	0.058	0.235
Income 15-20K	0.076	0.265
Income 20-25K	0.096	0.295
Income 25-35K	0.128	0.335
Income 35-50K	0.164	0.370
Income 50-75K	0.172	0.378
Income >75K	0.253	0.435
Age	52.711	16.315
Black	0.081	0.273
Asian	0.018	0.135
Hispanic	0.063	0.242
Native American	0.017	0.128
Other Minority	0.001	0.035
Female	0.619	0.486
Some High School	0.066	0.248
High School	0.304	0.460
Some College	0.265	0.441
College	0.330	0.470
Married	0.567	0.496
Divorced	0.142	0.349
Separated	0.023	0.149
Widowed	0.118	0.323
Partner	0.024	0.154
Self employed	0.090	0.286
Unemployed	0.040	0.195
Homemaker	0.079	0.269
Student	0.019	0.135
Retired	0.240	0.427
Observations	1,483,403	

Notes: Data from the 2005-2008 Waves of BRFSS